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Marketing insight from consumer reviews: Creating brand position through opinion mining approach

Mustafa Kemal Yılmaz [a], Hale Tuğçe Altunay [b,*]

[a] University of Samsun, Faculty of Economics, Administrative and Social Science, Department of International Trade and Business, Turkey
[b] Isparta University of Applied Sciences, Sütçüler Prof. Dr. Hasan Gürbüz Vocational School Management and Organization Department Logistics Program, Turkey

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ABSTRACT

Purpose: Brand managers can determine the ideas, perceptions, or experiences of consumers about their brands and their competitors through traditional marketing research techniques such as focus group discussions, surveys, and in-depth interviews. Through these methods, brands can observe the visual expression of consumer perceptions concretely by using perception maps or radar chart techniques. However, traditional methods have certain limitations. The validity of brand positioning in perception maps may be questioned since consumers' answers to survey questions can be misleading, consumers may express opinions about a product that they have not purchased yet, and other methods may divert the opinions of consumers at a specific stage.

In this study, global brand positions in the minds of consumers were concretized through perception maps by analyzing product comments on e-commerce sites through the use of opinion mining/sentiment analysis, one of the text mining methods. Moreover, perception maps and radar charts were created for the selected brands by forming the dataset from consumers' reviews about brands and products in online environments. perception map errors caused by traditional methods have been prevented by using opinion mining/sentiment analysis, which constitutes the originality of the research.

Design/methodology/approach: In this study, the text mining method, which includes opinion mining and sentiment analysis techniques, has been used to create perceptual maps from consumer reviews about products on e-commerce platforms. The TF*IDF method is used to identify the features to be compared in the perceptual map, which selects the features with weighted importance among the features mentioned by consumers in their comments. In this study, a lexicon-based opinion mining technique has been used to assign sentiment scores to consumers' comments on e-commerce websites for each product and its specified features.

Findings: The findings of the study have illustrated the areas in which the brands are evaluated as "insufficient" or "successful" by consumers within the framework of the characteristics selected in the study. It has been revealed that the method used in the research can provide accurate results for brand managers to make positioning decisions and develop effective marketing strategies.

Research limitations/implications: The research has been conducted by analyzing product reviews about selected brands on e-commerce platforms. The comments selected within the scope of the research include only those written in the Turkish language, and the evaluations have been carried out on the comments made until a specific date.

Originality/value: In this study, the analyses of the comments on the selected brands have ensured that the businesses are informed of the level of perception about their products in the market and that the research is based on a holistic approach that helps other consumers to develop a perspective on a specific product based on the comments of a consumer who shares his/her experience about the aforesaid product.

Introduction

With the acceleration of the concept of globalization since the 1980s, the world has become a single global village [1], which results in an increase in numerous factors such as the number of global businesses and product diversity (Bakırtaş et al., 2009). The innovation brought by

* Corresponding author.
E-mail addresses: mustafa.yilmaz@samsun.edu.tr (M.K. Yılmaz), halealtunay@isparta.edu.tr (H.T. Altunay).

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globalization and the resulting challenges has led businesses to try to keep up with the increasing competition in the world [2]. The efforts of businesses to resist competition have led to the production of numerous alternatives for a single product and to the continuous exposure of consumers to countless stimuli in environments where intense communication is experienced every day [3]. As a result, businesses have sought to gain a different position in the minds of potential consumers compared to their competitors [4]. Creating strong brand equity and a transparent and consistent brand image for consumers are among the important conditions for businesses to be in the "right" position in the minds of consumers ([5]: 79). The businesses should first determine the perception of their brands and products in the minds of consumers in order to address consumer perceptions "correctly" [6]. For this purpose, perceptual maps are the tool that provides the highest value to the business in positioning strategies. The advantage of perceptual maps for marketing managers derives from the concrete presentation of the perceptions of consumers in the market [7].

Traditional marketing research methods (surveys, interviews, etc.) are generally used to create perceptual maps (Karataş and Altunışık, 2015). However, the reliability of consumers' answers to survey questions is often a matter of debate. Expressing his/her opinion even though he/she has no knowledge about the brand he/she is supposed to comment on can be given as an example for this issue of reliability. Due to the limitations arising from traditional marketing research methods [8], it is aimed to solve the problem that arises in the creation of perceptual maps by taking into consideration the consumer product reviews that have accumulated on e-commerce platforms in recent years.

According to the "Digital 2021: Global Overview" Report, 66.6% of the world's population of 7.83 billion at the beginning of 2021 uses a mobile phone, while 59.5% uses the internet. Access the report here: https://datareportal.com/reports/digital-2021-global-overview-report [9]. The intensive use of the Internet in the world has reduced the distance between the buyer and the seller, and shopping can be completed in a shorter time through online sources [10]. Moreover, e-commerce has become a growing area due to the advantages of e-shopping such as the ability to do e-shopping at on-demand hours and the wide variety of products offered to consumers [11]. Thanks to the innovations brought to e-commerce platforms, consumers have been able to share their experiences about the product they have purchased with other consumers, and other individuals who do not have information about the product have started to be influenced by each other in terms of purchasing decisions. The growing number of consumer reviews on different channels such as forums, blogs, and e-commerce websites makes this data worth examining for businesses [12]. However, the manual processing of huge amounts of textual data, also called "Big Data", is almost impossible due to time and cost constraints for researchers to extract meaningful information from this database. Therefore, our study is based on the use of opinion mining/sentiment analysis algorithms, which include text mining and natural language processing techniques, to solve the above-mentioned problem.

In this context, the researchers have collected comments on 6 mobile phone brands selected from e-commerce platforms where consumers in Türkiye share their opinions after the purchase, they have used aspect-based opinion mining methods to determine the product features that help to compare brands in perceptual maps, and they have calculated sentiment scores for each comment using lexicon-based sentiment analysis approach. At the end of this process, they have positioned the scores obtained from the analyses to the coordinates of the relevant brand on the map in the perceptual maps created according to the features.

Concepts and theoretical background

Sentiment analysis/Opinion mining

Ideas are often based on subjective judgments as a result of emotions shaped around a problem, issue, fact, or thought. Expressing a personal opinion about a situation is one of the most common uses of oral and written communication [13]. Every behavior in our daily lives is the result of ideas; this is why ideas play an important role in the interaction between individuals. For this reason, when we want to buy a product or learn about a product we do not yet know about, we first seek the opinions of others [14]. In the past years, individuals used to communicate with the people in their immediate surroundings to fill this information gap, but today, thanks to the restructured updates of blogs, social media, and e-commerce platforms, they collect opinions from these platforms [15].

For example, with the emergence of global services such as e-Bay, TripAdvisor, and Amazon, most web users have gone from being mere users of web applications to actively becoming the center of these applications [16]. Therefore, the ideas that consumers share about products and brands on these platforms every day have accumulated and led to the emergence of collective intelligence [17]. However, the huge amount of unstructured content created by consumers makes it difficult to be analyzed manually [18]. In order to solve this problem, the concept of sentiment analysis, which is based on the automatic analysis of textual data in the web environment, was first introduced by Tetsuya and Jeonghee in 2003, and in the same year, Dave et al. started to use it as opinion mining [19].

Opinion mining studies are basically analyzed at three levels: (1) Document-Based, (2) Sentence-Based, and (3) Aspect-Based [20]. In document-based mining studies, the document to be analyzed is considered as a whole without being reduced to the sentence level and the opinions in the whole document are dealt with whether they are positive, negative, or neutral [12,21]. However, it is quite unreliable to draw a pure conclusion from these sources due to the large dataset of documents written in natural language text [22]. In sentence-based studies, it is decided to perform sentiment analysis on each of the sentences in the document rather than finding a single sentiment to represent the entire document. However, reviewers may write "Excellent" about one feature of the product and "Very bad" about another feature. Therefore, this level of opinion mining, which does not reflect the opinions expressed in different ways for product features, cannot provide deep information to the researcher [23]. At the level of aspect-based opinion mining, also known as goal-based opinion mining, the goal is to convey to the researcher directly the sentiment of each feature that the consumer writes about the product [20] and to determine the sentiment direction of each feature in the sentences that make up the entire document in the summary extracted from big data [24]. Hu and Liu [25] proposed aspect-based sentiment analysis for a more complete analysis to identify the positive or negative state of emotions for each feature.

Both in the aspect-based technique and in other opinion mining techniques, there are different methods for determining the sentiment of consumer opinions in analyzed documents [26]. These methods are categorized under two headings: (1) Machine Learning-based methods and (2) Lexicon-based methods [27]. It is observed that researchers mostly use Naive Bayes and Support Vector Machines algorithms among machine learning methods in opinion mining studies [26].

In this study, consumer comments on mobile phone brands were examined at the level of aspect-based opinion mining, and the sentiment expression of the comments made for each feature was embodied in perception maps by calculating the sentiment score by means of the lexicon-based method. For this reason, Section 2.2. will discuss the lexicon-based sentiment analysis approach.

Lexicon-based sentiment analysis

The lexicon-based approach is a method that involves the computation of the semantic aspect in words or sentences in a document [28]. The sentiment lexicon is the element needed for computation in this approach. The main task of the sentiment lexicon, which is also defined as an opinion lexicon, is to find the dictionary equivalents of the words in the document, classify them as positive, negative, and neutral, and assign a sentiment score to these words [25]. Since the beginning of sentiment analysis studies, many researchers have developed sentiment lexicons and made them available to users [29]. The most popular of these lexicons in the world is SentiWordNet, which mostly shows words with their synonyms and antonyms in lexicon-based studies on the English language. In this platform, a score is given for each word by checking whether the words used in the comments for all the features of the product have a dictionary equivalent, and at the end of the process, the sentiment pole and total score of the relevant sentence are determined by summing up all the sentiment scores given to the words in the sentence. For example, Lee *et al.* [30] used a goal-based approach to collect reviews about selected cell phone models from Amazon and PhonoArena websites and assigned sentiment scores to consumer reviews written in English using the WordNet dictionary. Kızılkaya [31], on the other hand, used sentiment analysis to interpret public opinions about political parties and their representatives in Türkiye by collecting tweets from the Twitter database and calculating the sentiment score of each tweet using the sentiment lexicon he created.

Perceptual mapping

In a competitive business environment, global brands need information from consumers to continue to operate and increase profits due to ever-changing external environmental factors related to customers, competitors, regulations, or countries [32]. In this sense, perceptual maps are visual diagrams that enable to illustrate where and how the brand and its competitors are positioned in the minds of consumers in the most effective way and to get the information needed by businesses when making brand positioning decisions in the context of strategic marketing [30]. Brand positioning techniques, referred to as perceptual maps or mind maps, are schematic tools for marketers to visualize competitive gaps in the market or consumer opinions about rival firms. Methods such as surveys, interviews, or text mining help to create and sustain a competitive advantage by obtaining customers' opinions about the brand [33]. They provide businesses using perceptual maps with a consumer-oriented perspective in achieving the ideal market position and enable them to make positioning decisions that differentiate them from their competitors [34].

Method description and opinion mining construction

The framework building

The figure below shows the steps involved in the design of the research:

Fig. 1 shows the general workflow to be followed in the research. The research suggests creating perceptual maps based on lexicon-based sentiment analysis from consumer reviews of the pioneer/flagship models that mobile phone brands offer for sale every year. In this study focusing on a systematic analysis, the six stages in the figure are divided into two basic stages in order to create perceptual maps: The first stage is to collect data on post-purchase experiences about the product and analyze them with text mining methods, and the second stage is to identify the product features that consumers mention most frequently with the help of a sentiment lexicon, score them and place them in their positions in perceptual maps Figs. 2 and 3.

Research scope

In the past, many products such as cell phones were mostly categorized in the group of "luxuries"; however, today, there has been a great increase in the number of businesses operating globally and of products

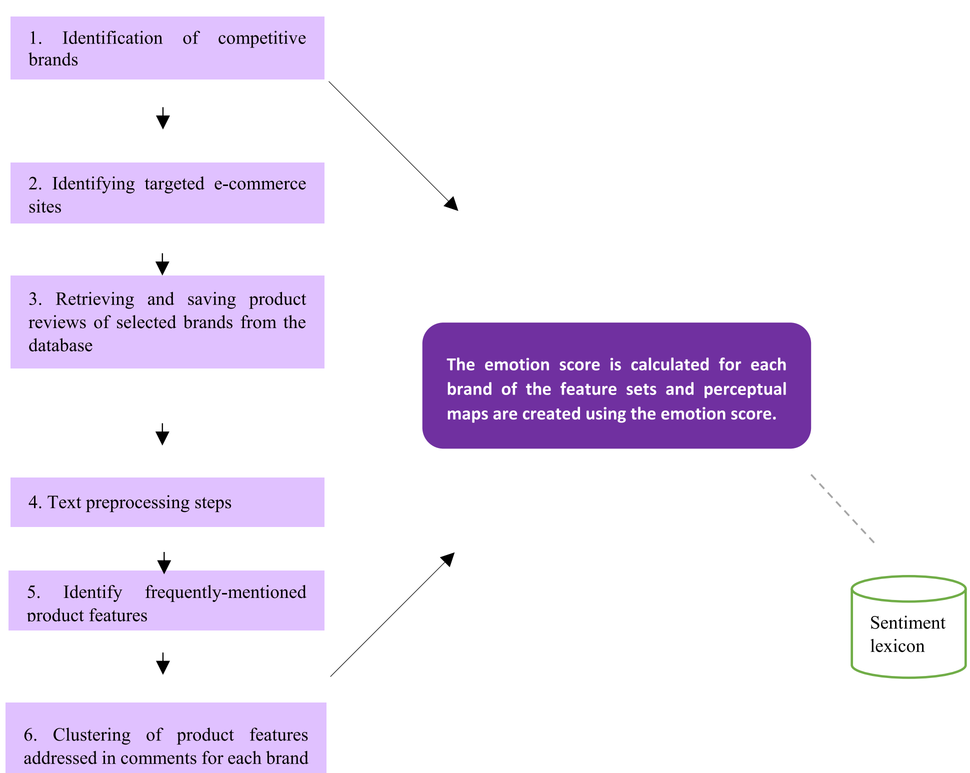

Fig. 1. Steps of research design.

produced by these businesses, and the products that are considered luxury have turned into the ones that can be easily purchased by everyone together with a constantly developing and self-renewing world understanding [35]. As a result, mobile phones have become a phenomenon that integrates with our daily lives [36].

The advantages of smartphones, such as offering a large number of product models that appeal to everyone, have driven global brands operating in this sector into intense competition with each other. By the end of 2020, the global smartphone penetration rate was 46.5%, and the number of smartphones sold worldwide reached 1 billion 380 million. Access the report here: https://www.statista.com/statistics/263437/global-smartphone-sales-to-end-users-since-2007/ [37]. Based on all these data, in our study, we will carry out a sentiment analysis for the comments on the selected brands and we will visualize the perception of the customers about the smartphone brands with the help of perceptual maps for the use of brand managers.

Since the opinion mining method will elaborate on the comments written in Turkish, the study included the brands with the highest market share in the Turkish market. According to Statcounter (https://datareportal.com/reports/digital-2021-global-overview-report (date of access: 17.04.2021) The cell phone brands with the highest percentage of market share in Türkiye are as follows:

The reviews written about the mobile phone brands listed above will be collected from e-commerce websites operating in Türkiye. Trendyol, Hepsiburada, N11, Gittigidiyor, and Amazon Türkiye were selected as the largest e-commerce websites in Türkiye within the scope of this research (Access the report here: https://www.eticaret.tv/haberler/icerik/turkiyedeki-en-buyuk-e-ticaret-siteleri/).

Determination of competitive brands

In addition to the main model determined by brands in the production and sale of phones, many different side models are offered for sale to satisfy the demands and needs of different market segments. This study focused on the leading models, colloquially referred to as “flagship” models that brands put on sale during the year. Since the products to be positioned in the perceptual maps at the end of the study should be up-to-date, we have selected the products that have recently entered the market and we have taken into consideration whether the number of comments about these products is sufficient. As a result of the evaluations, the phone models to be analyzed with the opinion mining method are listed below:

Collection of comments from websites

All consumer reviews written about the above-mentioned products were collected from the selected e-commerce websites (Trendyol, Hepsiburada, N11, GittiGidiyor, Amazon Türkiye) until the date of April 23, 2021.

The data was collected with the “Data Miner” program, a Google Chrome plugin. Data Miner is a Google Chrome extension that allows you to extract all comments (data) found on websites or social media platforms. The consumer comments were collected from 5 different e-commerce websites with the Data Miner program between the date when the selected products were listed on the websites and April 23, 2021. In this context, a total of 6081 comments were collected for the research and saved as CSV files in the Excel database. In the next step, 6081 comments on e-commerce websites were put through the text preprocessing process, which will be explained in the following section, to make them ready for analysis. Except for the extraction of data from the relevant web addresses, all stages were carried out in R software language.

Text preprocessing

Text preprocessing is the next step after the creation of the text collection. Proses are the main subjects of text mining, and they can be written in colloquial language. This reality has posed the biggest challenge due to the unstructured nature of text mining data compared to the structured data of data mining. Therefore, the texts have to go through a long pre-processing stage to extract information patterns from the data collected in the previous phase. This stage should inevitably be carried out with precision by the researchers for the output to be accurate. In this way, the text data will be cleaned and made more suitable for analysis.

The comments contain many spelling mistakes, emojis, irrelevant sentences, etc. that should be excluded from the dataset. The irrelevant data in the data set of this study consists of the contents that do not include any comment/opinion about any feature of the selected product in consumer reviews. In some websites where consumer reviews were obtained, the comments were only about *product sellers, cargo companies, fast or slow delivery of the product, or incomplete/incorrect delivery*. Therefore, at this stage, comments directly about the features of the product were selected, and “irrelevant” ones were excluded from the data set. As a result, the number of data to be analyzed decreased from 6081 to 3212. After this stage, the data became suitable for opinion mining methods.

Although the text preprocessing stage is a long process that requires time, it is an important process for the research to be conducted correctly. In this study, the R software program was used to prepare the data for analysis. The text preprocessing stage consists of subjecting the texts to different processes such as correcting spelling mistakes, separating words into their roots, removing punctuation marks and stop words, and Turkishization (Oğuzlar, 2011: 31).

- *Removal of Stop Words;*

In the comments, there are words such as “for, and, but, however”, prepositions and conjunctions that do not express any consumer opinion in sentiment analysis. At this stage, the comments in the “stopwords”

Table 1
Market shares of mobile phone brands in the Turkish market (%).

Samsung	Apple	Xiaomi	Huawei	Oppo	General Mobile
43,46	15,54	14,13	13,23	2,65	2,5

Table 2
The information of competing products.

Product/Info	Samsung Galaxy s20	iPhone 11	Xiaomi Mi Note 10	Huawei P30	Oppo Reno 4	GM 20 Pro
Total reviews	403	2934	273	397	784	1290
Time to market	Feb. 2020	Oct. 2019	Nov. 2019	March 2019	June 2020	August 2020
Period of reviews	until 23/04/2021	until 23/04/2021	until 23/04/2021	until 23/04/2021	until 23/04/2021	until 23/04/2021
Price (TL)	6000	8000	6000	6500	4000	2050
Rear camera	64 mp	12 mp	108 mp	40 mp	48 mp	48 mp
Front camera	10 mp	12 mp	32 mp	32 mp	32 mp	16 mp
Memory	128 gb	128 gb	128 gb	128 gb	128 gb	128 gb
Battery	4000 mAh	3110 mAh	5260 mAh	3650 mAh	4015 mAh	4050 mAh

Fig. 2. Stopwords list view in R program.

data set, which do not have any meaning for analysis in the sentiment analysis/opinion mining study to be conducted with the help of sentiment dictionary, were cleaned with the R software. The stopword list was introduced to R and the words in this list were extracted from the general corpus. The image below shows the representation of the stopword list in the R:

- *Text Normalization;*

In the text normalization step, which is one of the text preprocessing stages, spelling mistakes in the Turkish comments written in colloquial language were corrected. Since the comments written by consumers on e-commerce sites are often written in colloquial language, they are not written correctly. For this reason, spelling mistakes in the comments or keyboard-related errors such as using “i”, “u”, “c” instead of “i”, “ü”, “ç” were corrected in the text normalization step of the text preprocessing stage to carry out the analysis efficiently. To sum up, comments written in colloquial Turkish were converted into official Turkish to ensure the accuracy of the analysis.

This process was implemented through the use of the Istanbul Technical University Turkish NLP Web Service API. ITU NLP (Istanbul Technical University Natural Language Processing) is a research group established at Istanbul Technical University for different interdisciplinary studies that include text mining, data mining, natural language processing, and knowledge extraction. They develop software tools that can be used by researchers in the field of computational linguistics, including Turkish language and other languages (Eryiğit, 2014: 1). Using the Normalization method of the ITU NLP Web Service tool, errors in the data set that would affect the validity of the analysis, such as misspellings, were corrected and the text was normalized for all comments.

Using the Normalization method of the ITU NLP Web Service tool, errors in the data set that would affect the quality of the analysis, such as spelling mistakes, were corrected and the text was normalized for all comments. As a result of the observations made, the words/sentences that the ITU NLP tool could not provide 100% correction in the texts were edited manually.

After the Normalization method was applied to the entire dataset, the text was checked and errors were found that the service could not correct; in addition, some words could not be corrected and other words transformed into different words after the system was run. As a result of the examinations, the words that could not be corrected and transformed were edited manually. The table below shows example words that could not be corrected in the comments collected for the cell phone and the words that the system transformed:

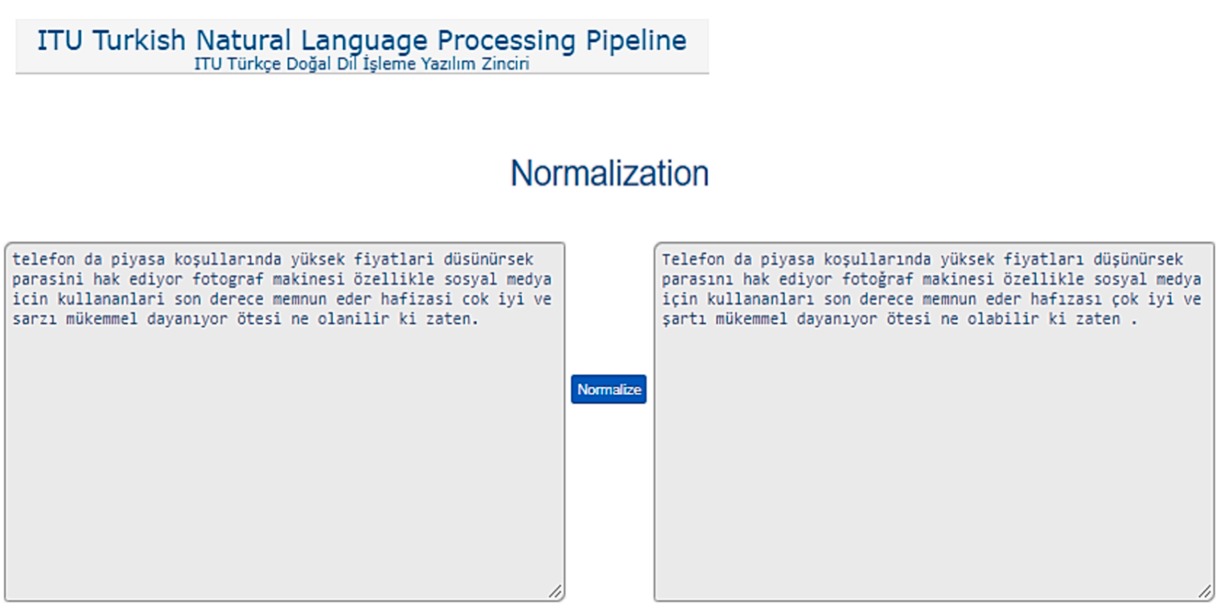

Fig. 3. Text normalization.

Table 3
Words edited by manual method.

words in the consumer comment	ITU NLP normalization result	with manual method edited result
Iphone	abone	iPhone
Samsung	samsun	samsung
camera	şamara	kamera
Iphone xr	İphone zer	iPhone XR

Feature selection

The aspect-based (goal-based) approach of Hu and Liu [25] was used to extract and cluster the product features mentioned in the comments and to efficiently find useful information for the research. In the aspect-based sentiment analysis approach, the aim is to identify the features of the product to be analyzed and to determine consumers' opinions about these features. Therefore, in aspect-based sentiment analysis research, it is necessary to determine the emotion-attributed features of the product, which is considered as an "entity" and which is identified as mobile phones in this study.

In this study, the aspect-based (opinion-based) opinion-mining approach proposed by Hu and Liu [25] was preferred to determine consumers' perceptions about the "product features" (price, performance, design, camera, etc.) of the 6 global mobile phone brands.

Based on the view that the product features that consumers mention the most in the consumer feedback on e-commerce platforms are the most important aspects for them [8], we used the TF*IDF method, which selects the most frequent and predominantly important features in the comments and which is frequently mentioned in the literature [38,39], to extract these features from the text document.

The purpose of preferring the TF*IDF technique in this study is not to analyze the words within each individual comment, each with different content, and extract features on a comment-by-comment basis; rather, it aims to scan all comments within the entire document and discover multiple features by assigning a statistical weight to each word appearing in each comment (aspect extraction) in relation to the total document. While BERT or another technique could be used to understand the prominent feature within a single comment, this study aims to determine the most prominent features within a dataset that encompasses all comments, rather than focusing on extracting features from a single comment. TF*IDF is preferred over BERT because it statistically weights the importance of words occurring within a document. In other words, instead of reducing it to a single comment for feature extraction, the aim is to emphasize the importance of a term within both a single comment and the total number of comments. Additionally, the BERT technique is oriented towards calculating the sentiment polarity of each consumer comment within the document (positive, negative, or neutral). This study goes beyond determining the sentiment polarity of consumer product reviews and assigns sentiment scores to each comment [40].

TF*IDF not only measures the number of times the term appears in the document, but also highlights the importance of the term for the document in numerical terms. That is, it emphasizes the importance of a term in a comment as well as in the total number of comments [41].

The R program was used to create the TF*IDF table within the scope of this study. After the TF*IDF list was generated, each term (74,254) presented by the algorithm was identified as a potential feature. These terms were then ranked according to the TF*IDF score and the terms that could be the features for the aforesaid cell phone models were selected according to the sample size and sentence length. For example, there are some terms that can or cannot be selected as features in reviews. While the terms "sound, storage, shoot, charge" can be features of a cell phone, words such as "good, product, telephone" do not have the quality to be included in the feature category.

At this stage, key terms/features related to the cell phone were explored to create perceptual maps. The TF*IDF approach, which quantifies the importance of the terms in the collection, is preferred for feature extraction. Accordingly, "price, design, battery, performance, sound, camera, processor, screen" were identified as the product features that would reflect the comparative positions of brands in the perceptual maps for mobile phones.

Table 4
The exemplary price feature set.

a competitive product in terms of price
Price is affordable
Too expensive
Expensive compared to other phones on the market
You could get a better flagship model for this price

Clustering

The main purpose of the feature extraction phase is to identify the features that will enable brand positioning on the perceptual maps. In this context, the features to be included on the horizontal and vertical axes of the map were determined as a result of the analyses conducted in the previous stage. The total number of comments on the 6 selected brands is 3212. It is not correct to say that consumers express opinions about only one feature of the product in the comments that constitute the dataset of the study. For example;

- *"camera and processor and screen are really nice if you are a gamer you need to charge it twice a day the price is good"*

- *"camera is great but looks a bit rough but still affordable"*

Many features of the phone are mentioned in these comments, and the statements carry different emotional states for each feature. Therefore, in this stage, a manual analysis was carried out on which feature of the product consumers expressed an opinion about, and the comment was included in the scope of the relevant set among all the feature sets determined in the previous stage.

At this point, an exemplary "iPhone 11′s Price Feature Set" will be depicted as follows:

This stage was applied to all brand reviews. The comments for the 6 brands were read one by one, and the sentence in the comment was assigned to the feature of that brand, whichever feature was commented on in the comments. Considering that there are 8 feature sets for 6 brands determined in the grouping stage performed by manual process, a total of 48 feature sets were created. In the next stage, sentiment scores were given to these feature sets by using a lexicon-based sentiment analysis approach, and then the numerical values were placed on the coordinates in the perceptual maps created according to the features.

Calculating opinion score for feature sets

There are multiple sentiment lexicons developed for the sentiment analysis approach in the literature. For example, Uçan's sentiment lexicon which he translated from English to Turkish in 2014, is one of the most basic lexicons in this field [42]. The present study was carried out with the use of the sentiment lexicon consisting of 49,241 terms aimed by Sağlam et al. [43] to be used for general purposes. Sağlam et al. [43] first created the "SWNetTR-PLUS General Purpose Sentiment Lexicon" with a volume of 37 K, including the common terms (4 K) that they identified by combining the dictionary covering 23 K terms by Uçan [42] and the 10 K dictionary developed within the GDELT project. Later on, they needed to develop a new lexicon due to the lack of capacity of the 37 K lexicon and the low performance of the present lexicon on the dataset. The current SWNetTR++ lexicon, which they created by adding words with synonyms and antonyms, contains 49 K terms. As a result of the analyses, it was concluded that the current lexicon gave better results compared to the previous one. Therefore, the SWNetTR++ lexicon developed by Sağlam et al. [43] was used in this study considering that its high volume would provide an advantage over other sentiment lexicons.

Each word in Sağlam et al.'s 49 K sentiment lexicon has an equivalent sentiment score. After the text preprocessing stages, each word in each comment in the data set consisting of 3212 consumer reviews was matched with the scores in this sentiment lexicon, and then the sentiment scores of the words in that comment were averaged, resulting in a total sentiment score for the relevant sentence/comment.

A sample diagram of how the sentiment score is assigned to each comment and each word within a comment in the texts consisting of consumer reviews is summarized as follows:

All comments in the feature sets of each brand were given a sentiment score, and then these scores were averaged and the result was the final numerical value of the relevant set of that brand. Tables 1-5.

The R software program was used to assign sentiment scores to the comments on each aspect/feature of the brands. The sentiment lexicon of Sağlam et al. [43] was first read into the program, and then the file was called from the program to assign a sentiment score to the comments in the relevant feature set. The same procedure was applied to 8 different feature sets of 6 brands.

Accordingly, the final score of each brand for each feature is shown in Table 6.

Building perceptual maps

The final stage of the research is the creation of perceptual maps to see the position of brands in the minds of consumers. By applying opinion mining methods to consumer comments about brands and their products, an average sentiment score was obtained from the selected features of the brands. The purpose of this process is to determine how cell phone brands are positioned in the minds of consumers in terms of various variables, which is the main subject of this study. The brands and their values obtained through the use of the sentiment lexicon will be used to place the brands on the horizontal and vertical axis to be positioned in the perceptual maps.

In this context, the variables to be placed at both ends of the perceptual maps were categorized into 2 groups and the perceptual maps were designed to show how consumers positioned the selected brands in their minds according to the groupings created within the scope of the research.

In the perceptual map below, price-performance features are categorized into 2 groups:

Table 5
Sentiment score assignment scheme to comments.

Consumer Reviews	Score of Words	Total Score of The Comment
Telefon seri hızlı	Telefon = 0,042,097,439 Seri = 0,077,151,742 Hızlı = 0,102,666,608	**0,221,915,789**
Batarya fazla ısınıyor kamera güzel	Batarya = 0,067,396,234 Fazla = 0,049,018,712 Isınıyor = 0,112,797,771 Kamera = 0,05,219,811 Güzel = 0,292,038,405	**0,573,449,232**

Table 6
Opinion scores.

Brands/ Features	Samsung Galaxy S20	iPhone 11	Xiaomi Mi Note 10	Huawei P30	Oppo Reno 4	GM 20 Pro
Performance	0,36	0,31	0,41	0,30	0.40	0.39
Price	0,30	0,21	0,25	0,33	0.33	0.29
Battery	0,01	0,12	0,16	0,20	0.15	−0.08
Processor	−0,06	0,19	0,16	0,24	0.17	0.10
Screen	0,49	0,26	0,47	0,41	0.44	0.39
Camera	0,38	0,27	0,38	0,38	0.35	0.36
Sound	0,26	0,30	0,16	0.45	0.38	0.25
Design	0,47	0,30	0,32	0.41	0.48	0.44
Average Score	0,28	0,25	0,29	0.34	0.34	0.27

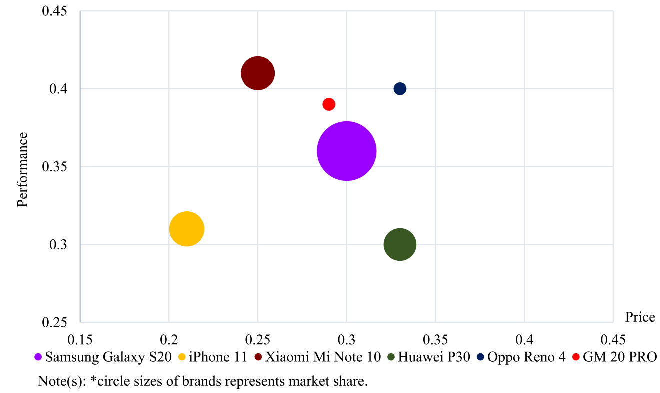

Fig. 4. Perceptual map for price and performance.

While the horizontal axis shows how consumers position the brands in their minds in terms of the "Price" feature of the product, the vertical Y-axis shows the perceptions on the "Performance" - also known as "Quality" for this study - of the phone models. In addition, the size of the circles in which the brands are positioned on the perceptual map represents the proportion of their share in the Turkish market. Fig. When the perceptual map in Fig. 4 is analyzed, Huawei P30 and Oppo Reno 4 models with the same sentiment score (0.33) are the brands that are in a more favorable position in terms of price compared to others. The phone models perceived as more "expensive" than other brands are iPhone 11 (0.21) and Xiaomi Mi Note 10 (0.25), respectively. In terms of the price feature of these models, the average price values were found to be lower because the comments mentioned that these products were expensive more frequently than other brands. In other words, those closest to the point of origin are more negatively positioned in the consumer's mind than the others.

The performance feature on the vertical axis shows where consumers position the brands by taking the average sentiment score of the comments where the product is described as "well-qualified" in the comments and in which the evaluations were made on the whole product, that is, its performance, regardless of a specific feature.

Accordingly, it can be said that Xiaomi Mi Note 10 is the brand with the highest performance compared to others (0.41) although consumers perceive this brand as relatively expensive (0.25). In other words, this brand, which the consumers position in their minds as the most expensive product after iPhone 11, is perceived as the brand with the highest performance. Xiaomi Mi Note 10 is followed by Oppo Reno 4 and General Mobile GM 20 Pro. Based on consumer reviews, it can be stated that Oppo and General Mobile are neck and neck in terms of quality. Compared to other brands, the Huawei P30 is the phone model that is positioned in minds as less qualified. This model of Huawei is perceived to be cheaper than other brands in terms of price, while there are negative opinions in terms of performance.

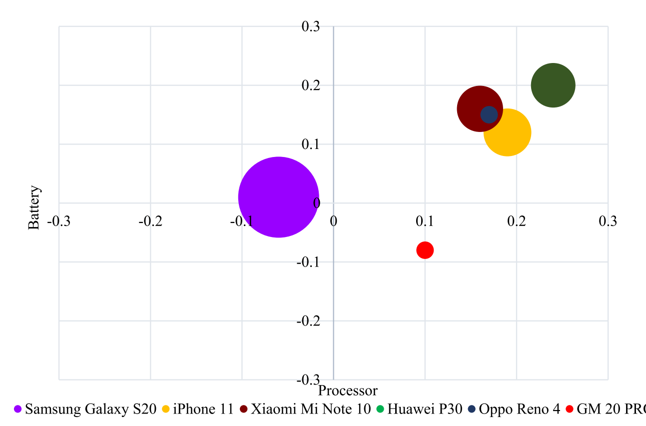

Fig. 5. Perceptual map for processor and battery.

In the perceptual map above, there are brand positions created according to consumer perceptions for two important features that are effective both in determining the price/marketing policies of businesses in the process from the production of the mobile phone product to its sale and in consumer purchasing decisions.

Processors are the brains that enable all electronic devices, especially smartphones, to perform their basic functions. For the mobile phone models that are the subject of this study, the processor is the main reason why consumers sometimes experience problems such as slowing down and freezing in the system which makes the transition between the operations performed on the phone fast and easy. Therefore, as indicated in the comments, it has been observed that the "Processor" feature has an important place in the purchase decision of consumers, and at this point, the position of the aforesaid feature in the consumer's mind was shown through a perceptual map by grouping it with "Battery" feature.

In terms of the processor feature, the Huawei P30 performed the best (0.24). When consumer evaluations have been analyzed, it is perceived that this product ensures a fast transition between transactions and has a processor that can be used easily by consumers who play games. iPhone 11 has been the second brand after Huawei in the processor ranking. Apart from the aforesaid two brands, Oppo and Xiaomi are respectively positioned better than General Mobile in terms of processor speed. The Samsung Galaxy S20 is positioned on the left side of the map with a sentiment score of −0.06 for this feature, which is quite poor compared to other brands' processor scores.

Based on the comments made according to how long the phone batteries last in daily use (used without charging for a long time), Huawei P30 is positioned on the perceptual map with the best battery ranking (0.27). Xiaomi Mi Note 10 (0.16) and Oppo Reno 4 (0.15) are the brands that are perceived to be in the best position in terms of battery after Huawei. iPhone 11 is perceived better in terms of battery than Samsung and General Mobile models, but more negatively than the previously-mentioned 3 brands. This situation shows that the iPhone 11 is situated in the middle position in terms of the battery feature among all brands. When the comments about the battery of the iPhone 11 model have been examined, it has been seen that the brand has continuously improved this feature in its new models over the years and that it performs well above the battery performance of its older models. The Samsung Galaxy S20 model has been positioned closer to the origin on the map compared to other brands, as in the processor feature, and this has confirmed that the relevant brand has resulted in a weak perception in the consumer mind in terms of both the battery and the processor.

Radar charts

Perceptual maps are widely-used marketing tools to show where brands are positioned in the minds of consumers for specific aspects. In this study, the eight features determined to see where the selected brands are positioned in the minds of consumers have been positioned according to their sentiment scores in the perceptual maps by forming groups of 2. The limitation of the method is that perceptual maps only show the brand locations based on two features placed on the horizontal and vertical coordinates of the map. In this study, radar plots will be used to fill the gap created by the perceptual maps as they show multiple product features at the same time. Both perceptual maps and radar charts are important tools for businesses to make effective and competitive decisions within the framework of strategic marketing planning [30].

Table 7 below shows the two clusters calculated using the average scores of all brands within the scope of the features selected according to the sentiment scores. The brands were divided into two clusters and then displayed comparatively in radar graphs because product features were compared by being displayed only on two axes - x and y - in perception maps, and therefore multiple perception map graphs emerged.

In this study, radar charts will be used to fill the gap created by the detection maps as they show multiple product features at the same time. If many products were shown at the same time, the lines representing all products would overlap and the graph would not be easily read. For this reason, it is necessary to limit the number of products shown on the radar charts. In addition to showing multiple features at the same time, radar charts differ from perceptual maps in terms of displaying only a limited number of products/brands on a chart.

In Table 7, two radar charts were created by limiting the number of products (brands) as the perception maps were incomplete to compare brand positions in the context of multiple features. A clustering approach based on the average of all feature sentiment scores was used to determine the brands to be displayed in the same graph.

The researchers ranked the top three brands with the highest "nearly-the- same- score" (Huawei, Oppo and Xiaomi) among the 6 global brands' average sentiment scores in Table 6 and the three brands with the lowest average (Samsung, Galaxy, iPhone) and they formed these two clusters, and they obtained two scores by averaging the averages of these brands with the averages of the brands in both clusters. In the radar graphs below, the clustered brands were compared in terms of all features Fig. 5.

The three brands in the first cluster have higher average scores than the brands in the second cluster in terms of all features.

The radar graph in Fig 6 visualizes the brands with the highest sentiment scores in terms of all features of the brands obtained as a result of lexicon-based sentiment analysis studies. Accordingly, Oppo Reno 4 is the brand that covers the widest area of the three lines in the radar graph. This shows that the Oppo brand provides more favorable results in the selected product features compared to the other two brands. According to this graph, Oppo Reno 4 has dominated its competitors in almost all features except the processor. Contrary to the positive situation of the Oppo Reno 4 model, the Xiaomi Mi Note 10 is the brand that occupies the least space in the graph and is represented by the red line. Except for the performance and display features of the Xiaomi Mi Note 10, all other features were negatively commented on in consumer reviews. This can be easily seen in the perceptual maps in Fig. 6 and Fig. 7.

The radar graph in Fig. 7 visualizes the lowest average sentiment scores of the brands obtained as a result of lexicon-based sentiment analysis studies. Accordingly, Samsung, iPhone and General Mobile models have lower scores than the brands in Fig 7. In the radar chart (aka spider web chart) above, the iPhone 11 is the brand with the

Table 7
Brand sets.

Brand sets	Average sentiment score
First Cluster: Huawei P30, Oppo Reno 4, Xiaomi Mi Note10	0.32
Second Cluster: Samsung Galaxy S20, GM20 PRO, iPhone 11	0.26

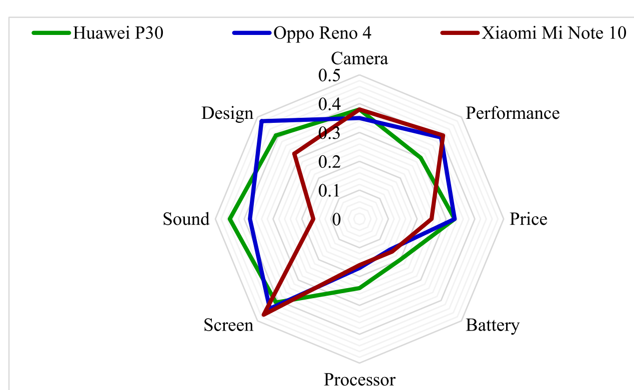

Fig. 6. Radar chart: First cluster.

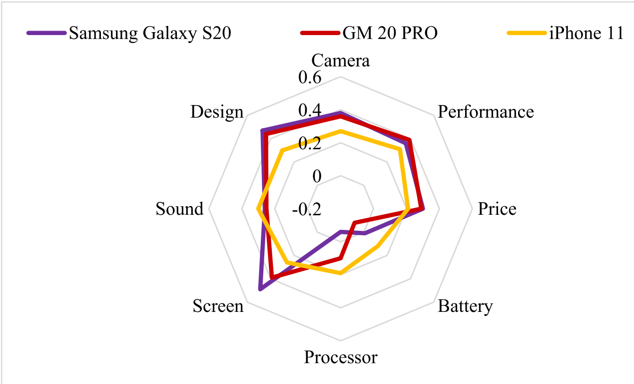

Fig. 7. Radar chart: Second cluster.

smallest footprint. The Samsung and General Mobile brands are very close to each other in this sense. Accordingly, with the exception of the processor and audio features, the iPhone model is in a poor position compared to its two competitors. Samsung Galaxy S 20 and GM 20 Pro models are very close to each other in terms of all other qualities except processor and battery.

Conclusion

Opinion mining is the process of extracting consumer opinions from reviews in textual format on the Internet. Consumers' expressing their opinions about a product or a topic using colloquial language is the main subject of opinion-mining analyses. Consumers' opinions about brands and their products in specific categories have provided great opportunities for businesses to recognize customer perceptions and feedback in a less time-consuming and cost-effective way, away from traditional and time-consuming customer feedback surveys. Research based on online product reviews not only provides businesses with considerations for product improvement, repricing, or repositioning but also provides a reference for global brands to analyze consumer perceptions of post-purchase experience.

In this study, the comments made by consumers on e-commerce sites about the mobile phone models selected within the scope of the study have been examined with opinion mining techniques based on text mining, and the brand positions in the minds of consumers have been visualized with perceptual maps and radar graphs. The perspective of this study is to enable global brands to capture customer insights based on opinion mining to assist in customer-centric product development strategies. This methodology, which combines opinion mining and perceptual mapping techniques, provides businesses with accurate and effective strategic marketing information to learn the position of their own brand and competitors' brands in the minds of consumers.

Since the data language used in the study is Turkish, the mobile phone brands with the highest market share in Türkiye are included in the scope of the study. In addition to identifying competitive brands, a lexicon-based sentiment analysis approach has been used to score consumer comments according to their sentiment, and brands have been positioned on perceptual maps according to their scores. The methodology used in the study has been applied to consumer reviews on the websites of Trendyol, Hepsiburada, GittiGidiyor, N11, and Amazon Türkiye. With the help of the TF*IDF algorithm, it has been discovered which features of the product consumers most frequently commented on, and then these features have been placed in groups on the perceptual map axes.

The main motivation for using this method is to convert consumers' post-purchase experience from online qualitative text format to quantitative data. By sharing their experiences, consumers not only act as voluntary sales agents for cell phone brands but also provide information to reduce the decision-making risks for consumers. It is thought that the product positions in both indicators will provide brands with an opportunity to evaluate their relationship with their competitors in terms of their product features.

Contributions to management

Qualitative data obtained from reviews is considered a source of customer insight and can enable better creation of brand positioning strategies. For example, when a company wants to enter the market with a new product, it can potentially benefit from brand reviews to understand consumers' perspectives on this product. These reviews can be found not only on the platforms where the product is sold but also on social media, forums, and blogs. By focusing on the perceptions of the new product, marketers can better illustrate the effect of the positive brand image in their advertising and communication efforts. With the help of automatic perceptual maps based on the comments, it can be measured by using the previous data whether the position of the brand for the consumer has changed and whether the positioning efforts have increased the brand image. Moreover, this method will create a great opportunity to see the gaps in the market and will also provide businesses with the opportunity to avoid the fields that are dangerous in the minds of consumers.

In the past, businesses used techniques such as traditional surveys or focus groups to determine customers' perceptions of their products and competitors. The difference between the method used in this study and the traditional methods provides advantages to businesses in several ways. First of all, consumers may not have any past experience or even any knowledge about the brand asked in the perceptual map developed with the survey method; this may be misleading for the position of the brand on the map. However, in a comment-based method, the consumer who comments is someone who has already used the product and shared their experience. Therefore, any inaccuracy in the analysis on the part of the reviewer/consumer is out of the question here. Online evaluations are written in the colloquial language of consumers, so they accurately reflect their satisfaction, desires, and concerns about the product, unlike inaccurate and incomplete answers in the questionnaire. This is due to the fact that there is user confidentiality in the comments and consumers openly express what they think about the product to other consumers who may buy the product.

Using these new approaches, brand managers can use the perceptions collected in customer reviews as a valuable source of input for future positioning decisions. The most accurate and effective marketing decisions can be made by means of the user experience and perception of the purchasing process shared by consumers on the relevant platforms. The new product, new price, new market, and new location created through R&D strategies can be channeled into the brand mantra to create a stronger brand image and identity. In addition, identifying the perceptions of consumers in different country markets about the products of brands competing in the global market can make important contributions to the development of positioning strategies.

Contributions to consumer

The first behavior that consumers exhibit before purchasing a product, regardless of having any information about the product, is to go through the reviews of other consumers on these platforms. With digitalization, online reviews on websites have become the first source that consumers consult before making a purchase decision. In these environments, other consumers who share their experiences and opinions about the use of a specific product provide guidance for consumers who are in the phase of purchase decision. For example, if the reviews about the product are negative, the consumer may give up buying the product; on the contrary, if the reviews are positive, the consumer may decide to buy the product. In this sense, online reviews contribute to businesses obtaining the target market perception of the product, while providing information/advice to consumers in a way that will affect their purchasing decisions. Especially in technological products where risk perception is higher, user experiences help consumers to make the right decision. Within the scope of the study, 6081 product reviews have been collected from the selected e-commerce sites, and the dataset has been reduced to 3112 by deleting irrelevant comments during the clustering process. The sentiment scores of the comments found with the opinion mining method have been placed on the perceptual maps in terms of the selected features, and the brand positions in the consumer mind have been visualized. As a result, the contribution of the study to consumers is thought to minimize the risk that may be experienced in the purchase decision process by analyzing product reviews based on scientific methods and providing the information needed by consumers who will choose between these brands. In addition, it is expected that the effectiveness of consumers who comment on e-commerce platforms to reflect mass market behavior will motivate other consumers to share more insights by encouraging other consumers. In this way, customer perceived value in the purchasing processes of technological products, where the customer perceived risk is quite high, are positive.

Limitations and directions for future research

This study has some limitations as in other studies in the literature. First of all, this study is based on aspect-based sentiment analysis about specific features of mobile phones. 8 features were identified for the brands analyzed in the study, and the comments were categorized according to these features. However, it was observed that some comments were also made about the features not covered in this study although most of them included the selected features. In addition, the comment reviews were scored by the lexicon-based sentiment analysis method with the help of the sentiment lexicon created by Sağlam et al. [43]. Although the scope of the sentiment lexicon used in the study was large (49 K), if a word mentioned in the comments was not included in the lexicon, no sentiment score could be assigned to that word.

To summarize, in lexicon-based opinion mining, the researcher needs a sentiment lexicon that contains a high proportion of the words in the database and provides the mathematical equivalent of these words. However, the biggest limitation of this method is that the sentiment lexicon is created for general purposes and some of the words in the content of the study do not have any equivalent in the sentiment lexicon. In such a case, that word cannot be given a sentiment score and the accuracy rate of the study may decrease. For this reason, it is thought that in future studies, different results may be obtained through the analysis conducted by choosing any of the other sentiment analysis techniques in the literature.

Although the methodology is based on consumer reviews, in practice, the sample preferred for creating perceptual maps or radar charts can easily be used to analyze reviews of other products. Since it is not clear who made the comments collected in this study, no information could be obtained about the demographic data of the commenters. It is thought that a broad perspective on brand positions can be developed based on demographic data in future studies. Besides, this study examines the phone brands with the highest market share in the Turkish market. Therefore, the data language was Turkish, and foreign language comments about the same brand were excluded from the scope of the study. It is considered that taking into account the interpretations made in different languages in future studies will make significant contributions to the literature. Also, the perceptual map created within the scope of the study only reflected the perceptions found in the comments made up to April 23, 2021; therefore, it is not indefinite. For this reason, it means that future changes in consumer perceptions about the brand will also alter the values in perception maps and radar charts.

As a final point, the cell phone models selected for the study are the "flagship" models that brands launch simultaneously with their competitors every year. However, global brands offer many other cell phone models throughout the year. The analysis of consumer comments on these different models would also be useful to businesses.

Declaration of Competing Interest

I declare that there is no conflict of interest in relation to this research article. I have no financial or personal relationships with other people or organizations that could inappropriately influence this research.

Data availability

Data will be made available on request.

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